Government
Institute for
Economic Research

Working Papers 28

Informational Efficiency of the EU ETS market – a study of price predictability and profitable trading

Piia Aatola

Kimmo Ollikka

Markku Ollikainen

Working Papers 28 March 2012

VATT WORKING PAPERS

28

Informational Efficiency of the EU ETS market – a study of price predictability and profitable trading

Piia Aatola

Kimmo Ollikka

Markku Ollikainen

Valtion taloudellinen tutkimuskeskus
Government Institute for Economic Research
Helsinki 2012

Piia Aatola, Government Institute for Economic Research VATT P.O.Box 1279 FI-00101 Helsinki. Email: firstname.surname@vatt.fi

Kimmo Ollikka, Government Institute for Economic Research VATT P.O.Box 1279 FI-00101 Helsinki. Email: firstname.surname@vatt.fi

Markku Ollikainen, Department of Economics and Management, P.O. Box 27, FIN- 00014 University of Helsinki. Email: firstname.surname@helsinki.fi

This paper is a part of the research consortium Electricity Markets, Emissions Trading and Incentives in Bioenergy Technology (BEET) funded by the Academy of Finland (Grant No. 124480).

ISBN 978-952-274-015-1 (nid.)
ISBN 978-952-274-016-8 (PDF)

ISSN 1798-0283 (nid.)
ISSN 1798-0291 (PDF)

Valtion taloudellinen tutkimuskeskus
Government Institute for Economic Research
Arkadiankatu 7, 00100 Helsinki, Finland

Edita Prima Oy
Helsinki, March 2012

Cover design: Niilas Nordenswan

Informational Efficiency of the EU ETS market – a study of price predictability and profitable trading

Government Institute for Economic Research
VATT Working Papers 28/2012

Piia Aatola – Kimmo Ollikka – Markku Ollikainen

Abstract

We study the informational efficiency of the European Emissions Trading Scheme, EU ETS market by simulating the trading in this emerging market. If the market is efficient, profitable trading should only exist locally in time. We adopt the Timmermann and Granger (2004) definition of efficiency and for the first time in the literature run a large set of econometric, technical analysis and combined models to forecast the emissions allowance price changes. These forecasts are then used as trading signals in the trading simulation. We find that the combined models outperform the other models in forecasting ability. Trading simulation based on models combining time series and technical analysis trading rules shows that there have been possibilities for profitable trading in the EU ETS market during the study period of 2008–2010. This suggests that the EU ETS market shows periods with no informational efficiency.

Key words: European Union emissions trading, informational efficiency, econometric analysis

JEL classification numbers: Q52, Q53

Tiivistelmä

Tutkimme Euroopan unionin päästökauppamarkkinoiden informaatiotehokkuutta kaupankäyntisimulaation avulla. Sovellamme Timmermannin ja Grangerin (2004) määritelmää informaatiotehokkuudesta. Markkinat ovat informaatiotehokkaat, jos kaupankäynti markkinoilla tuottaa taloudellista voittoa vain satunnaisesti. Estimoimme suuren joukon ekonometrisia aikasarja-analyysiin perustuvia, teknisen analyysin sekä näitä yhdistäviä malleja ennustamaan päästöoikeuden hinnan muutoksia. Näin saatuja hintaennusteita käytetään kaupankäynnin signaaleina simulaatiossa. Tulokset antavat viitteitä siitä, että vuosina 2008–2010 päästökauppamarkkinoilla olisi ollut mahdollisuuksia ei-satunnaisiin taloudellisiin voittoihin. Parhaiten malleista toimivat yhdistelmämallit, jotka yhdistävät aikasarja-analyysia ja teknistä analyysia.

Asiasanat: Euroopan unionin päästökauppamarkkinat, informaatiotehokkuus, ekonometria

JEL-luokittelu: Q52, Q53

Contents

1. Introduction

Fama (1965) defines an efficient market as one with a large number of rational, profit maximising, actively competing agents, each trying to predict the future market value, and all having important current information almost freely available. The question on market efficiency is of special interest in the emerging and developing markets. The European Union Emissions Trading Scheme, EU ETS, creates a framework for the new and evolving market. The purpose of the EU ETS is to provide a cost-efficient market-based instrument for emission reductions. Cost-efficiency of the EU ETS requires a well-functioning and mature market, i.e. a market that is liquid and informational efficient.

The EU ETS has, however, many properties that may call into question the efficiency of the market. Firstly, it is a novel endeavour and also the largest emissions market so far. Emissions trading markets, by their nature, are based on political decisions. Due to the uncertainties in the international climate policy, the foundations of the EU ETS are not solid. Secondly, the key participants in the EU ETS are electricity producing companies. These companies face the ongoing electricity market deregulation process in Europe and have thus varying competence and experience to act in competitive markets depending on the state of the deregulation (Weigt, 2009). Besides, electricity markets and consequently the EU ETS market are fairly concentrated. Both these markets have a few companies with large market shares. This causes a concern of oligopolistic competition. Finally, the market has been functioning for only a few years and, particularly, recent issues of VAT fraud and IT attacks have raised questions of the functioning of the market and the efficiency of price formation. Nevertheless, since the beginning of the trading, from 2005, volumes and numbers of traders have increased rapidly, and so has the liquidity of the market. (PointCarbon, 2010)

In this paper we investigate the informational efficiency of the EU ETS market. If the market is informational efficient, the best prediction of the next period's price is the current price; the rest of the price evolvement is just white noise. Thus, predicting the price of the EU Emission Allowance (EUA) provides no systematic economic profits, meaning the returns can cover the risk premium and transaction costs at the most. These definitions of informational efficiency stem from theories introduced in the late 1960s and early 1970s. Seminal contributions are by Roberts (1967), Fama (1970) and Jensen (1978), who describe the market to be efficient if the price in the market reflects all information and adjusts immediately to any new information.

Informational efficiency of a market has been given many definitions. Roberts (1967) classifies informational efficiency into three forms with the corresponding information sets. First, if the information set includes only the history of prices or returns themselves, then the market exhibits weak form efficiency. Second, semi-strong form efficiency occurs when the information set includes all publicly available information. Third, efficiency is strong form efficiency if the information set includes all public and private information. Fama (1991) takes a slightly different route and extends the first category (weak form efficiency) to a more general set of tests for return predictability implying that the information set includes also other series than the assets' own price history. Moreover, according to Fama, the semi-strong efficiency includes only event studies. That means testing the statistical significance of different events, like publishing corporate reports or important pieces of economic news, on the price or returns. Indeed, since then event studies have been very common in securities market efficiency studies (see e.g. Groenewold and Kang, 1993) but they have also been applied to commodities markets (see e.g. Gross, 1988).

We examine in this paper informational efficiency of the EU ETS market by focusing on the first category, that is, the return predictability of Fama's division of informational efficiency. In contrast to the weak form efficiency or event studies, examining the predictability has no standard test procedures. We base our analysis on the innovative definition of efficient markets provided by Timmermann and Granger (2004):

> *"A market is efficient with respect to the information set, X_t , search technologies, S_t , forecasting models, M_t, if it is impossible to make economic profits by trading on the basis of signals produced from a forecasting model in M_t defined over predictor variables in the information set X_t and selected using a search technology in S_t."*

Following this definition we use, for the first time in the emissions trading literature, trading simulations as a means of examining the informational efficiency. In our trading simulation, the information set, X_t, includes price series that most probably are connected to the EUA price, such as electricity prices or fuel prices. Search technology, S_t, refers to the model selection criteria and the choice of buying and selling signals. Thus, our model set, M_t, and trading strategies consist of a large number of strategies that traders could have adopted in the EU ETS markets. We use three set of models: 1) technical analysis models, 2) fundamental-based regression models and 3) GARCH models.[1]

Fang and Xu (2003) provide a useful approach to run the trading simulations. Drawing on an analysis of daily Dow Jones Averages over the first 100 years,

---

[1] Extension of the information set, X_t, to cover also other aspects than the asset's own price history is always conditional on the researcher's choices and thus there is a possibility for bias: What information should be included? Which variables should be chosen for the fundamental analysis? In the asset price modeling the information set is often extended by macro- or micro-level variables like dividend yield, T-bills and T-bonds as well as growth and inflation rates. (See e.g. Pesaran & Timmermann, 1995.)

they show that combined forecasting models of technical trading rules and time series forecasts outperform both of the rules when they are used separately. They also argue that technical trading rules are more capable of identifying periods when returns are positive and time series forecasting are better in identifying periods when returns are negative. Following Fang and Xu (2003), we run models that combine technical analysis and time series models, but we depart from their analysis by running, in addition to AR models, multiple time series models with the fundamentals where Fang and Xu (2003) use only AR models.

Our analysis is based on weekly data. We find at least three reasons for this. Firstly, by Sandoff and Schaad (2009) and Jaraite et al. (2010) the EU ETS compliant traders are acting more on a weekly than on a daily basis. Secondly, in trading it is crucial to act before the information on which the signal is based on assimilates to the market. This adjustment period, meaning the time between the signal and price adjustment is longer in the weekly based trading than in the daily based trading and offers a longer period for profitable trading. Thirdly, even if we miss some information of the daily observations we can instead include a longer information horizon by using weekly data in our simple regression models.

Despite the short history of the EU ETS, some empirical studies analyzing the price formation and the informational efficiency already exist. Most of them cover the first phase of the EU ETS[2]. Studies analyzing the price formation find the predictability of the EUA price and returns to be rather weak when studied by either time series analysis (Benz and Trück, 2009; Paolella and Taschini, 2008) or by fundamentals analysis (Mansanet-Bataller et al. 2007; Alberola et al. 2008; Chevallier 2009). Creti et al (2012) study the carbon price drivers and equilibrium in phases I and II. They find stable, but differing cointegrating relationships for both periods. Hintermann (2010) analyses under the assumption of efficient market the relation of the EUA price to the marginal abatement costs. His findings are in line with the previous studies that under the phase I the price did not follow the marginal abatement costs closely.

The first studies of the informational efficiency in the EU ETS are by Daskalakis and Markellos (2008), Milunovich and Joyeux (2010) and Chevallier (2009). These papers test the weak form informational efficiency and find no clear evidence of efficiency in any form in the first phase. Montagnoli and de Vries (2010) study both phases I and II EUA prices with variance ratio tests. Their results show signs of market efficiency under phase II. Miclaus et al. (2008) use

[2] The first phase of the EU ETS was 2005–2007, the second 2008–2012 and the third 2013–2020. The first phase was considered as a “learning-by-doing” period and the initial allocation of the EUAs was generous. The first publication of the emissions data in May 2006, an important event for the EU ETS market, showed how quickly information is absorbed by the market. As the information on the great surplus of allowances was revealed, the market reacted in a couple of days. In a week the price crashed from almost 30€ close to 5€ and after a month the EUA2007 had almost no value at all.

the event study methodology to examine the effect of the announcements of the national allocation plans and the publication of emissions verifications on the carbon prices. They find that the market is efficient during the first phase. Conrad et al. (2012) also study the EUA price adjustment to news announcements. They use a high frequency intraday data and by modeling the volatility they conclude that EUA price adjusts well to the news of economic development. In addition, in a corresponding market, the US SO_2 market, Albrecht et al. (2006) found evidence of the weak form informational efficiency.

To our knowledge this is the first study to examine the efficiency and in particularly predictability of the EUA price using a trading simulation. We find that if traders have used a large set of models in their trading analysis toolbox and, especially, combined them, profitable trading during the first years of the EU ETS has been possible indicating that the market has not been informational efficient. The results give insights into the progress of the new climate policy market mechanism. The rest of the paper is as follows. Section 2 describes the EU ETS market and data used. Section 3 describes the models and the Section 4 the results of the trading simulation. Section 5 concludes.

2. The EU ETS market data

We employ data on the price series of the EUA and different fundamental price series that the theory suggests to have an impact on the EUA price and thereby would help forecasting the EUA price. The role of fundamentals in determining the demand and thus the price of EUA is well established in the literature (see e.g. Christiansen et al. 2005; Alberola et al., 2008; Rickels et al., 2007; Hintermann, 2010; Fezzi and Bunn, 2009). As the electricity sector is the biggest single sector in the EU ETS, the electricity price is an important fundamental for the EUA price. The abatement possibilities are central for the EUA price development. The most important single, short-term emissions reduction possibility for the electricity sector is fuel switching. By fuel switching we mean changing the fuel in the electricity production. Usually this means changing coal for a less emitting gas. Delarue and D'haeseleer (2007) estimate the impact of fuel switching for the EUA price determination. To capture the fuel switching effect we have the gas-coal price difference and the spread prices in our data set.

For EUA series we use next year's forward contract maturing in each December. For electricity prices we use yearly forwards of the German baseload price and the NordPool system price. The set of fuel prices includes the UK winter gas forward, yearly API2 CIF ARA forward coal price, and the North Sea Brent Crude oil forward. [3] The gas-coal series, that is the difference between coal and gas prices, is a proxy index for the short-term abatement by fuel switching. Clean dark spread and clean spark spread are the spreads between the German baseload electricity price and the fuel cost when using coal and gas, respectively. In addition we include a stock market index FTSE 350 to describe the economic activity in general and volume series (EUA) to catch the market activity of the EUA market. The key variables of the data are presented in Table 1.

[3] The API 2 price is the primary price reference for physical and over-the-counter (OTC) coal contracts in northwest Europe. Some 90% of the world's derivatives are priced against the Argus/McCloskey API2 and API 4 indexes. CIF ARA means coal delivered to Amsterdam, Rotterdam and Antwerp inclusive of costs, freight and insurance.

Table 1. *Data*

Series	Specification	Origin
EUA	EU ETS allowance, forward	ECX EUA Futures Contract
NOPO	NordPool electricity system price, forward	NordPool
ELDE	German baseload electricity, forward	EEX, German power exchange
OIL	North Sea, Brent Crude oil, forward	ICE
GAS	UK gas price, winter forward, UK NBP	IPE GBP/therm
COAL	Coal price, forward, API2 CIF ARA	MCCLOSKEY OTC-market
GASCOAL	GAS-COAL	
CDDE	Clean dark spread = German baseload electricity - (coal + EUA)	EEX, German power exchange
CSDE	Clean spark spread = German baseload electricity - (gas + EUA)	EEX, German power exchange
FTSE	FTSE 350 Index, a market capitalisation weighted stock market index	London Stock Exchange, Yahoo! Finance
VOLUME	Weekly volume of the EU ETS allowance	ECX EUA Futures Contract

Source: ThomsonReuters and Yahoo! Finance, 2010

We use the weekly forward data of all series with observations from each Wednesday[4]. Forward data is used as forward contracts are the most liquid commodities in the EU ETS market (State and trends of the Carbon Market, 2011). In Figure 1, the level series are plotted for the study period from June 2006 to December 2010. Figure 2 describes the log returns.[5] We omit the time period before the great crash in the EUA prices in May 2006. Since then the market has been more stable and the impacts of institutional and political decisions have diminished. The period June 2006 – December 2007 is used to

[4] Particularly, we use Wednesday observations to avoid the possible weekday anomalies. There is evidence of returns being abnormal on Mondays and Fridays in the stock markets (see e.g. Gibbons and Hess (1981) and Cross (1973)).

[5] The level series of the Clean spark spread includes some negative values and we have taken only the first difference. Furthermore, in the trading simulation, volume data is treated in a way that only observations of the growing volumes were taken into the estimation. In addition, the positive log returns of the volume series are multiplied by minus 1 if the EUA return is negative during the same week. By this we want to control the increased volatility of the EUA forward price approaching its maturity date.

estimate models and trading simulation is conducted during the latter part of the study period, i.e. January 2008 – December 2010. Tables A1a and A1b (in the Appendix) describe the data in more detail with the descriptive statistics

As can be seen in Figures 1 and 2, the energy markets have been rather volatile. Generally, prices showed an upward trend until mid-2008, when the first signs of the economic turmoil started to emerge. Thereafter electricity and fuel prices together with the EUA price decreased strongly. Electricity prices in Central Europe and the Nord Pool area are closely related but the Nordic electricity price level is lower. Oil and gas prices, which are often indexed, reached record high levels in summer 2008. The price of coal has been stable for a long time, including the beginning of the study period, but it started to increase rapidly in 2007 and 2008. This makes the GASCOAL ratio relatively low. Figure 2 suggests that the volatility and price changes increased during the end of 2008. The overall economic activity in the EU started to recover during the first quarter of 2009 and the slight economic growth boosted the fundamental prices as well. The EUA market volumes also gained a peak in mid-2010. Carbon prices have been fluctuating between 12 and 15 euros for almost two years now and the latest economic crisis has led the price to decrease under 10 €.

Figure 1. *Time series data in the forecasting models (May 2006–December 2010).*

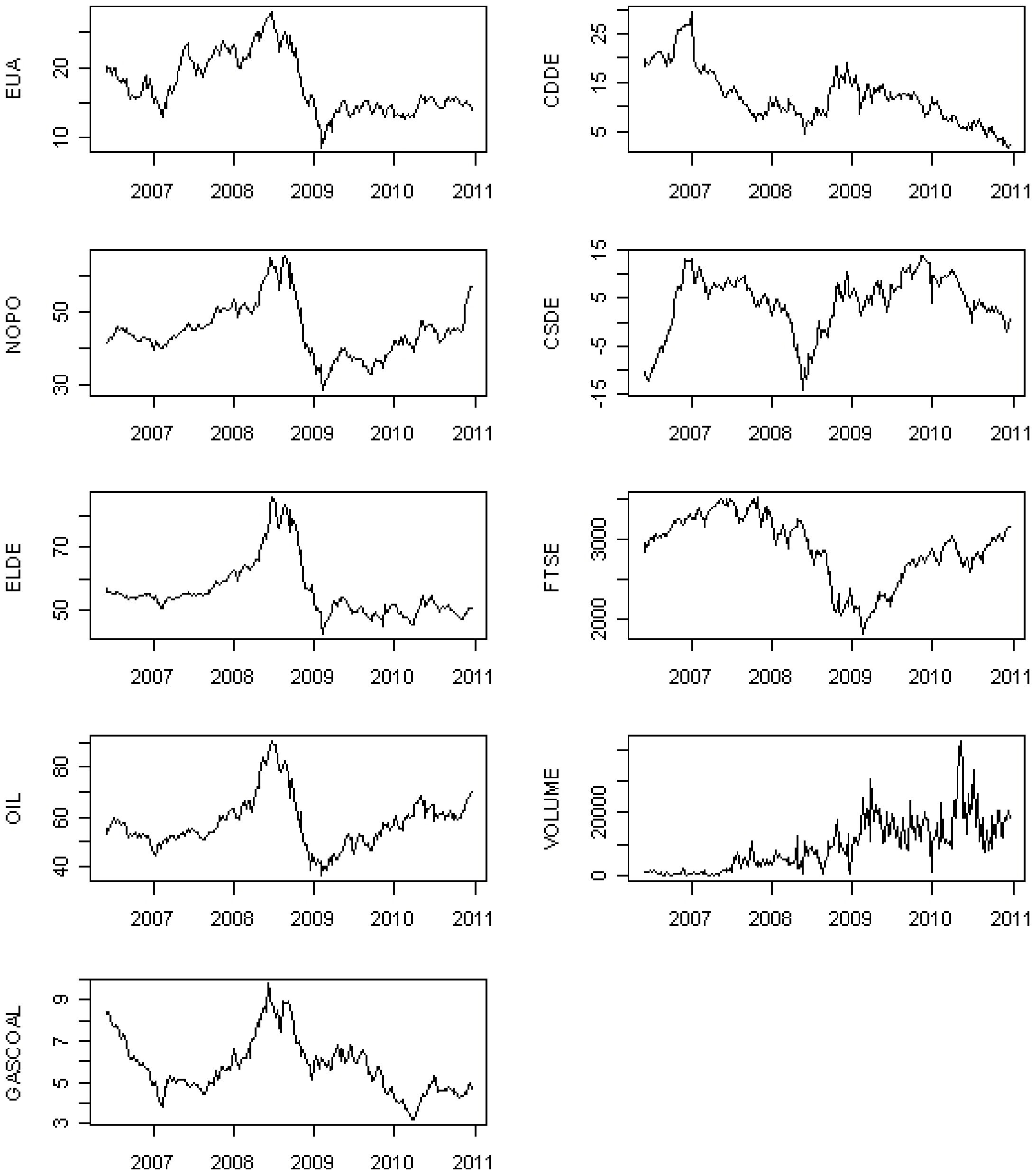
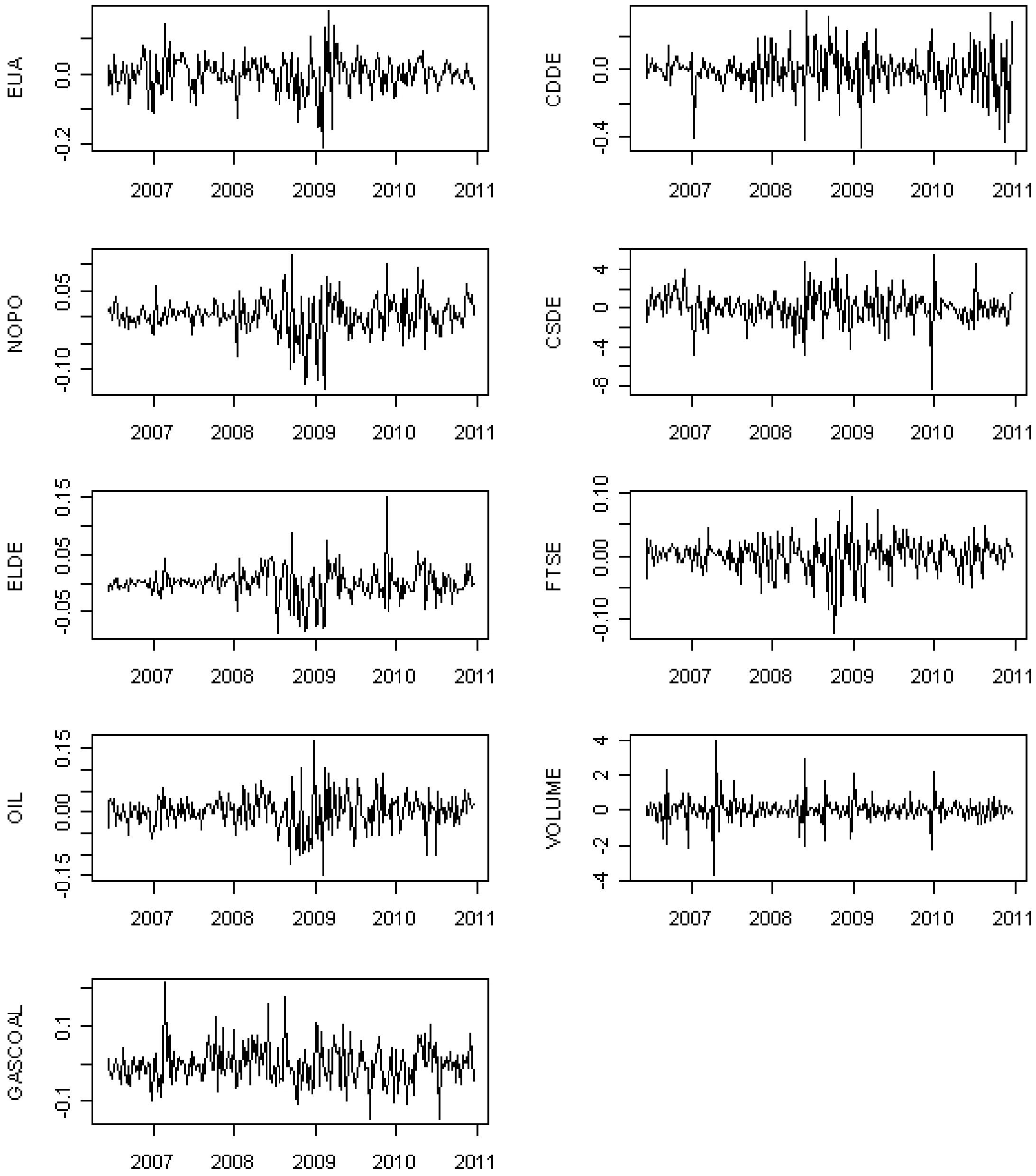


Figure 2. Log returns (May 2006–December 2010; CSDE: first difference).[6]



[6] In the trading simulation, volume data is treated in a way that only observations of the growing volumes were taken into the estimation. By this we want to control the increased volatility of the EUA forward price approaching the maturity date. In addition, the positive differences of log volume series are multiplied with minus 1 if the EUA return is negative during the same week.

3. Predictability of EUA price – trading simulation

Trading in the EU ETS market has two objectives. On the one hand, compliant companies adjust their production and abatement decisions according to the EUA market price. In competitive markets this results in a cost-efficient allocation of allowances. On the other hand, companies intend to manage their carbon portfolio in an optimal way. In the EU ETS the agent's carbon portfolio has a value determined by the current EUA price. If the agent assumes that the price of the forward contract is going to rise, for example, over a one-week horizon, it is optimal to buy some contracts today and sell them next week at a higher price, and vice versa if the price is expected to drop. The more accurate the prediction of the short-run fluctuations of the EUAs, the higher the earnings in the emission trading markets.

In this section we introduce the trading simulation to mimic the EU ETS trading and see if there has been profitable trading during the first years of trading. With help of these findings we can, referring to Timmermann and Granger (2004), assess the efficiency of the market. An informational efficient market is a necessary condition to achieve the cost-efficiency target of the policy instrument. Thus in the following as we study the informational efficiency of the market we indirectly assess also the cost-efficiency of EU ETS.

Our trading simulation is based on price forecasting models that produce trading signals for buying or selling. Forecasting models are built upon time series regression models and technical analysis. Time series models include regressions of EUA price return on histories of the EUA's own return and also returns of other market fundamentals presented in the previous section. In the spirit of Timmermann and Granger (2004) we describe in what follows the used model set M_t as well as the search technology S_t. We present here in this section the basic ideas of the models. After that in the next section we will present and discuss the results.

We use the out-of-sample forecasting method, where trading signals are calculated in "real time" during every trading day. Thus, the simulation imitates the actual week-based trading during the trading period by adding a new observation in every week and searching for the best model to forecast the next week's EUA price change with the new information set. We are not after the most sophisticated forecasting model candidate or any causal relations between variables but wish to establish a realistic search technology for producing trading signals for a fictitious investor in the EU ETS market.[7]

[7] See, for example, Box and Jenkins (1976), Hamilton (1994) and Lütkepohl (2007) for the state of art forecasting models.

3.1 Models

Fundamental analysis

Models of fundamental analysis are simple regression models that try to capture the historical relationship between the EUA price and its fundamental elements. Hence, following Timmermann and Granger (2004), the model set in the fundamental analysis includes regression models that have different combinations of fundamental variables and their lags from the information set X_t. The models are in general of the following form

$$\begin{aligned} \Delta X_{1,t} = \beta_0 + \beta_{11}\Delta X_{1,t-1} + \ldots + \beta_{1j_1}\Delta X_{1,t-\hat{j}_1} \\ + \beta_{21}\Delta X_{2,t-1} + \ldots + \beta_{2j_2}\Delta X_{2,t-\hat{j}_2} \\ \vdots \\ + \beta_{k1}\Delta X_{k,t-1} + \ldots + \beta_{kj_k}\Delta X_{k,t-\hat{j}_k} + \varepsilon_t \end{aligned} \quad (1)$$

$$\Delta X_{i,t} = \ln(X_{i,t}) - \ln(X_{i,t-1}), \quad (2)$$

where $\Delta X_{i,t}$ is the dependent variable, the log return of the EUA. The explanatory variables, that is, the lagged log returns of the fundamental variables, are denoted by $\Delta X_{i,t-j}$ where $i = 1,...,k$ denotes the series, $j \in \left(1, 2, ..., \hat{j}_i\right)$ denotes the lag and $\hat{j}_i$ denotes the total number of lagged log returns of the fundamental variable i in the model. The regression coefficient β_{ij} describes the historical relationship between the explanatory variable $\Delta X_{i,t-j}$ and the dependent variable $\Delta X_{1,t}$. The error term ε_t includes all the variation that the explanatory variables are not able to capture in the model. Our model set includes a maximum of 3 lags of 9 different price series or indexes. Each model can thus be characterized by a vector $m_{xt} = \left(\hat{j}_1, \hat{j}_2, ..., \hat{j}_9\right)$, where $\hat{j}_i \in \left(0,1,2,3\right)$. If $\hat{j}_i = 0$, the variable i is omitted from the regression equation. [8]

GARCH models

Looking at the return series of the prices (see Figure 2) we notice that there is some volatility clustering especially in late 2008. To catch this clustering, we tested different GARCH models to fit the data and we end up using the GARCH(1,1) model. Models used in the GARCH forecasting are presented originally by Bollerslev (1986) and Engle (1982). GARCH(*p*,*q*) is a model for

[8] With all regressors included in the model the regression equation includes, with the constant term, 28 regressors and the whole model set includes 262,144 different model combinations.

the general autoregressive conditional heteroscedasticity where q is the order of the autoregressive term and p stands for the moving average term. Models used in the analysis are in general of the following form

form

$$\Delta X_{1,t} = \phi Z_t' + \varepsilon_t \tag{3a}$$

$$\sigma_t^{\ 2} = \omega + \sum_{i=1}^{p} \alpha_i \varepsilon^2_{\ t-i} + \sum_{j=1}^{q} \beta_j \sigma^2_{\ t-j}\,, \tag{3b}$$

where X is the dependent variable and Z is a matrix of explanatory variables in the mean equation (3a), σ^2 is the conditional variance of the error term that is regressed on its lagged values and the lagged values of the squared error term of the mean equation (3b).

For the mean equation in GARCH models given by (3a) we have two different specifications: an AR(1)model and a model with all explanatory variables lagged one period, abbreviated FU.[9] A similar analysis is made in some recent papers analysing the price behaviour of the EUA. Chevallier (2009) analyses macroeconomic effects of the returns in the EU ETS and also Paolella and Taschini (2008) suggest using GARCH models for modelling the EUA prices. Benz and Trück (2009) use AR(1)-GARCH(1,1) modelling for the spot prices.

We also use the GARCH-M (Engle, Lilien and Robins, 1987) and EGARCH-M (Nelson, 1991) models to capture the volatility clustering in the price series. These models allow studying the relationship between the market risk and expected returns. Financial theory suggests that an asset with a higher risk would pay higher return on average (Dimson et al. 2002). In the GARCH-M models the conditional variance of return is added as an independent variable in the mean equation to explain the conditional return. δ in (4a) captures the effect that the higher variability in ε_t has on the return. We use the GARCH-M model that is described with the following equations:

$$\Delta X_{1,t} = \phi Z_t' + \delta \sigma_t^{\ 2} + \varepsilon_t \tag{4a}$$

$$\varepsilon_t = \sqrt{\sigma^2}\, v_t \tag{4b}$$

$$\sigma^2_{\ t} = \varsigma + \alpha_1 \varepsilon^2_{t-1} + \alpha_2 \varepsilon^2_{t-2} + \dots + \alpha_m \varepsilon^2_{t-m} \tag{4c}$$

[9] Hence, using a vector characterization the used mean equations of the GARCH models can be defined by vectors AR(1)= (1,0,…,0) and FU(1)=(1,...,1). To save space we abbreviate the models as AR- and FU-.

Equations (4b) and (4c) describe the error term and the volatility that is often convenient to have in this form of ARCH(m) process which imposes assumptions about the serial dependence of ε_t . v_t is an i.i.d. sequence with zero mean and unit variance.

The exponential general autoregressive conditional heteroskedastic (EGARCH) model by Nelson (1991) is another extension of the GARCH model. EGARCH models allow the volatility to react in an asymmetric way to the volatility changes. It has been shown empirically that the volatility tends to rise in response to a decrease in returns and fall in response to an increase in returns (see e.g. Pagan and Schwert (1990), Engle and Ng (1993)).

As earlier, let $\varepsilon_t = \sqrt{\sigma^2} v_t$. Now the conditional variance for an EGARCH in MA(∞) form is

$$\log(\sigma_t^2) = \omega + \sum_{k=1}^{\infty} \beta_k g(v_{t-k}) \tag{5a}$$

$$g(v_t) = \theta v_t + \lambda(|v_t| - E(|v_t|)) \tag{5b}$$

or equivalently in ARMA(p,q) form

$$\Delta(L) \log \sigma_t^2 = \omega + \Psi(L) g(v_t) \tag{5c}$$

with lag-polynomials of $\Delta(L)$ and $\Psi(L)$ of order p and q respectively.

Equation (5b) shows the asymmetric relation between returns and volatility, the character of the EGARCH. This is caused by the fact that $g(v_t)$ is a function of both the magnitude and the sign of v_t.[10]

As (5a) and 5(c) describes $\log(\sigma^2)$ the σ^2 will be positive and in contrast to GARCH model no restrictions on estimation is needed. Further, we run models that combine the GARCH-M and EGARCH model specifications. These models are noted with EGARCH-M.

Technical analysis

Technical analysis is a commonly used method to forecast changes in the financial markets. It includes several different kinds of models and trading rules. We test the profitability of one popular technical analysis trading rule: the variable length moving average (VMA). Daskalakis and Markellos (2008) used the same

[10] See Nelson (1991) and St. Pierre (1998) for detailed discussion.

trading rule while investigating the efficiency of the EU ETS in the period 2005–2006.[11] For example, with the variable length moving average VMA(1,30) rule, a buy signal is given if the one-week moving average (current price) is lower than the 30-week moving average. Thus, the trader will buy the EUAs and sell them back in the next period. If the current price is higher than the moving average, the trader will sell the EUAs and buy them back in the next period. In our simulations we use three different specifications, namely a one-week window for a shorter estimation period and 10-week, 30-week and 50-week windows for a longer period (abbreviated VMA10, VMA30 and VMA50 respectively).

Combined models

In addition to the above-mentioned models, we examine a combination of trading rules, namely, the rules based on different technical analysis together with the time series forecasts, i.e. fundamental analysis rules and rules by the GARCH models. As shown by Fang and Xu (2003), the technical trading rules are more capable of identifying periods when returns are positive and time series forecasting rules are better at identifying periods when returns are negative.

3.2 Search Technology: model selection rules

Search technology refers to the rules and criteria, on which the model selection and the trading signals are based. In the following we describe the model selection in more detail for the fundamental analysis and GARCH models. We then discuss about the trading filter that shows whether a trading signal leads to an actual trade.

In the fundamental analysis we use basic statistical model specification criteria to pick the best model in each week. Hence, in every week we add a new observation, calibrate models, calculate four model selection criteria, choose the best models with respect to different criteria and generate forecasts for the price change based on the best models.[12] Finally, trading signals generated by the forecasts are used in the trading, if the trading filter allows it. The model selection criteria include rolling and recursive root mean square forecasting error (RMSFE), Bayesian information criterion (BIC) and adjusted R^2. The choice of the model selection criteria is not, however, straightforward. Inoue and Kilian (2006) state that using information criteria (IC) would be consistent, under suit-

[11] Daskalakis and Markellos (2008) found evidence of profitable first and second phase futures trading. They also checked the profitability of another trading rule, namely trading range break-out (TRB). With the rule of TRB(1,30) a buy (sell) signal is generated if the current price is lower (greater) than the minimum price during the 30-week window. In our simulation TRB rules turned out to be really unprofitable and the results are not reported.

[12] To ease the computational burden, we, in fact, use a two-stage process in the model selection. In every eight weeks we choose best 500 models with respect to the BIC value and fix the model set for these models for the following eight-week period.

able conditions, with choosing the best forecasting model, whereas calculating the RMSFE (rolling or recursive) might end up suggesting over-parameterized models.[13]

Searching the best GARCH models we use the maximum likelihood estimation with the log-likelihood and Schwarz information criterion for the model selection. Eight specifications were chosen: AR-GARCH, AR-EGARCH, AR-GARCH-M, AR-EGARCH-M, FU-GARCH, FU-EGARCH, FU-GARCH-M, FU-EGARCH-M.[14] Every week during the trading simulation the models are calibrated and coefficients updated by maximum likelihood estimation when running the recursive forecasts. We use the Marquardt maximizing algorithm and the normal distribution. The models assume normal distribution of error terms and the back casting parameter is set at 0.7.

However, one must note that predictability invalidates EMH only if the yardstick for testing EMH is measured in economic profits (Timmermann and Granger, 2004). Due to this requirement, we use a trading filter in the trading simulation. This filter guarantees that trading takes place only when it is expected to be profitable: the profits in trading must be risk adjusted and cover the transaction costs.

Firstly, transaction costs in the EU ETS have been approximately 10–15 cents in OTC trading and fewer than five cents in exchanges per one EUA traded. The level of ten cents is approximately 0.5% of the average price of the EUA during the trading period. We use that as a yardstick for the transaction costs. Secondly, the returns should also cover the risk premium, which is not observable and is varying in time (Timmermann & Granger, 2004). To give a lower bound for an annual risk premium, we use 5% as a proxy.[15] Thus, at the weekly level the risk premium proxy is 0.1%.

Hence, in order to make profits in the long run, the average return of the trading must exceed at least 0.6% in weekly trades. Thus, in the trading simulation, a trading filter of 0.6% is used. For example, if the forecast by a time series model predicts the change of the EUA price to be less than 0.6%, no trade is carried out. However, the EUAs are bought or sold whenever the forecast is above a 0.6% price rise or drop. With the technical analysis rules trading occurs only when the

[13] Pseudo out-of-sample forecasting is used to evaluate the forecasting power of the model. We use recursive and rolling methods. Recursive RMSFE is calculated by first reducing the original sample of observations by 15% and forecasting the omitted values with this shortened model. Rolling RMSFE is calculated in the same manner as in the recursive method except that the number of observations included in the regressions is kept constant. In our models the forecasting window is 30 weeks.

[14] All models refer to lag order of one. E.g. AR(1)-EGARCH(1,1).

[15] This is a relatively low risk premium. Nevertheless, due to the economic downturn the reference for the risk-free rate, the yield of 3-month Germany Treasury bill for example, has been on average during the estimation period 1.5 % but with a huge variance from 3.2 % to 0.25 %.This is also a relatively low rate. Besides, we use the 5% proxy as an upper bound for the risk-free rate when calculating the Sharpe ratio. Thus, the values of the Sharpe ratio are biased downwards.

short-period moving average (current price) is over the 0.6 % band of the corresponding long-period moving average during the estimation window. With combined models a buy (sell) signal is generated if both rules give buy (sell) signals. Otherwise no trade is made.

4. Results

In the trading simulation, forecasts for the EUA are made with weekly data for every week in the period of January 2008–December 2010. Thus, there are 157 trading days in twelve yearly quarters. In the portfolio management simulation an agent buys EUAs with some fixed amount of money every Thursday morning. If the price is predicted to rise by the forecast, the trader buys and sells if the price is predicted to fall (and if the trading filter allows the trade). The following Wednesday, the agent will sell or buy back the same amount of allowances. If the signal was right, the agent gains a profit from the actual price difference between the two prices, but if the forecast was wrong, the agent will suffer a trading loss. If there is no signal at all, the trader will do nothing. We assume that the agent would not even invest the money at the risk-free rate. This makes the results downward biased and this affects e.g. the cumulative return and Sharpe ratio. We assume that the amount of the investment is fixed for the whole trading period and the profits are not reinvested.

In Tables 2a and 2b we present some profitability indicators of the trading for the whole trading period (January 2008–December 2010) for all strategies. *Signals* for trading indicate either to buy or to sell. *Winning trades* is the number of trades when the forecast and the actual price move in the same direction and the trading filter allows the transaction. This should be as big as possible. *Profitability index* is the ratio of the winning trades to the number of all trades and it should be over 50%. *Profit factor* is the ratio between the total profits and total loss of the trades. In order to make a profit, the profit factor should be greater than one. *Average return* is the average of the weekly returns of the trades made and *cumulative return* is the total (yearly) return on the investment. To reap a profit in the allowance market, the average return should be more than the risk-free rate plus transaction costs and the cumulative return as big as possible.

We also calculate the *Sharpe ratio* establishing a lower bound on the variation in the stochastic discount factor scaled by its conditional mean to measure how much the risk premium varies in time. The Sharpe ratio is calculated as the excess return over the risk-free rate divided by the standard deviation of the returns in trading: the higher the Sharpe ratio, the lower the risk and the higher the profit with the used trading strategy.

Table 2a. Results of the weekly trading simulation with trading signals with a 0.6 % trading filter (2008–2010)

	R2	BIC	Rolling RMSFE	Recursive RMSFE	AR-GARCH	AR-EGARCH	AR-GARCH-M	AR-EGARCH-M	FU-GARCH	FU-EGARCH	FU-GARCH-M	FU-EGARCH-M
Signals	114	84	95	110	10	13	41	55	110	110	112	118
Buy signals	53	34	37	53	2	4	27	42	57	53	59	40
Sell signals	61	50	58	57	8	9	14	13	53	57	53	78
Winning trades	59	52	50	55	5	5	21	31	66	63	68	62
Profitability index	51,8 %	61,9 %	52,6 %	50,0 %	50,0 %	38,5 %	51,2 %	56,4 %	60,0 %	57,3 %	60,7 %	52,5 %
Profit factor	1,07	1,82	1,48	1,10	0,88	1,18	0,83	1,21	1,57	1,49	1,54	1,17
Average return	0,13 %	1,10 %	0,80 %	0,20 %	-0,50 %	0,51 %	-0,42 %	0,43 %	0,83 %	0,74 %	0,80 %	0,29 %
Cumulative profit / year	4,9 %	30,7 %	25,0 %	7,3 %	-1,6 %	2,2 %	-5,7 %	7,8 %	30,1 %	26,9 %	29,7 %	11,4 %
Sharpe ratio	0,02	0,16	0,11	0,03	-0,01	0,02	-0,03	0,04	0,14	0,12	0,13	0,05

	VMA10	VMA30	VMA50
Signals	149	148	154
Buy signals	80	72	77
Sell signals	69	76	77
Winning trades	67	72	80
Profitability index	45,0 %	48,6 %	51,9 %
Profit factor	0,91	1,14	1,19
Average return	-0,19 %	0,25 %	0,33 %
Cumulative profit / year	-9,5 %	12,2 %	17,1 %
Sharpe ratio	-0,04	0,04	0,06

Table 2b. Results of the weekly trading simulation with a 0.6 % trading filter with combined models

VMA30 +	R2	BIC	Rolling RMSFE	Recursive RMSFE	AR-GARCH	AR-EGARCH	AR-GARCH-M	AR-EGARCH-M	FU-GARCH	FU-EGARCH	FU-GARCH-M	FU-EGARCH-M
Signals	45	31	39	44	2	2	21	32	41	45	41	50
Buy signals	22	8	17	22	2	2	18	26	21	22	21	18
Sell signals	23	23	22	22	0	0	3	6	20	23	20	32
Winning trades	24	20	20	23	2	1	12	18	25	25	25	27
Profitability index	53,3 %	64,5 %	51,3 %	52,3 %	100,0 %	50,0 %	57,1 %	56,3 %	61,0 %	55,6 %	61,0 %	54,0 %
Profit factor	1,38	2,67	1,86	1,28	inf	0,49	0,81	1,22	2,57	1,81	2,39	1,43
Average return	0,67 %	1,81 %	1,18 %	0,51 %	0,52 %	-0,32 %	-0,58 %	0,56 %	1,58 %	1,17 %	1,50 %	0,65 %
Cumulative profit / year	10,0 %	18,5 %	15,2 %	7,5 %	0,3 %	-0,2 %	-4,0 %	6,0 %	21,5 %	17,4 %	20,4 %	10,7 %
Sharpe ratio	0,07	0,15	0,12	0,05	0,09	-0,05	-0,03	0,03	0,17	0,11	0,16	0,07

From Table 2a, of all trading strategies technical analysis (VMA10, VMA30 and VMA50) produces the largest number of signals. This implies that the market has been rather volatile. However, the returns are not high with this trading strategy and the low Sharpe ratios indicate the riskiness of these strategies. The volatility clustering in the market implies a need for GARCH modelling. Most of the GARCH models are profitable and some of them belong to the most profitable models. Especially the GARCH models with fundamental mean equations perform well. The fundamental analysis models are good compared to technical analysis. Models based on the rolling RMSFE and BIC criteria are profitable by all indicators. The signals are in general divided quite equally into buying and selling signals. However, especially with the profitable fundamental models the selling signals have occurred more frequently.

Combined models in Table 2b generally outperform even the best fundamental strategies with respect to the profit indicators. Only the worst GARCH models combined with the technical rule are not profitable with all indicators. With the combined models the number of trading signals is reduced considerably, as a trade takes place only if both rules allow. The reduction of the trading days raises the concern of the bias of the results. Instead of constant profit making, one single trade might have affected the profits significantly. For the result robustness it is favourable to have more rather than fewer trading days (see e.g. the pure and combined rolling RMSFE profit factors). Thus, one has to be careful in interpreting the results. However, as we see from the Sharpe ratios, the riskiness of the pure strategies is generally higher than of the combined trading rules. Note also that we assume traders not to invest in risk-free assets during the periods when they do not trade in ETS market. This will exert downward bias on the results of the models with only a few trading signals.

Exceptionally high but risky returns are typical in new and developing markets where the informational efficiency is still improving and where the chance of excess profits is high. (Dimson et al., 2002). This is clearly the case in our study as well. The cumulative yearly returns, approximately 15 % to 20 %, are much higher than the average stock market returns. The long-term average stock market return is 5%–10 % (Dimson et al., 2002). And the Sharpe ratios of the models are low compared to the long-term averages in the stock markets. For example, in the calculations on the US stock markets the Sharpe ratios have been between 0.7 and one (Dimson et al., 2002).

Table 3 presents the annual cumulative profits of each model. We see that only five out of the total 27 models show negative annual cumulative profits. We find similar results as Fang and Xu (2003): the models regarded as time series models (fundamental analysis models and GARCH models) generate losses during the periods when the EUA has risen and profits during the downward movements and vice versa for the technical analysis trading strategies.[16] This observation explains why the combined models with all the fundamental analysis rules turn out to be profitable.[17] Note that, even though the choice of the combined models is made ex post, the results are very robust. For example, if we change the technical rule in the combined models to VMA50 and use the models of fundamental analysis for the time series rule, the trading still remains profitable. Even the VMA10 rule, showing bad results as a pure trading strategy, is profitable when combined with the rolling RMSFE model (see Appendix for details).

[16] Some of the worse GARCH models are not in line with this result. We also have a significantly smaller sample than Fang and Xu (2003)

[17] Recursive RMSFE is only marginally profitable with the 0.6 % filter.

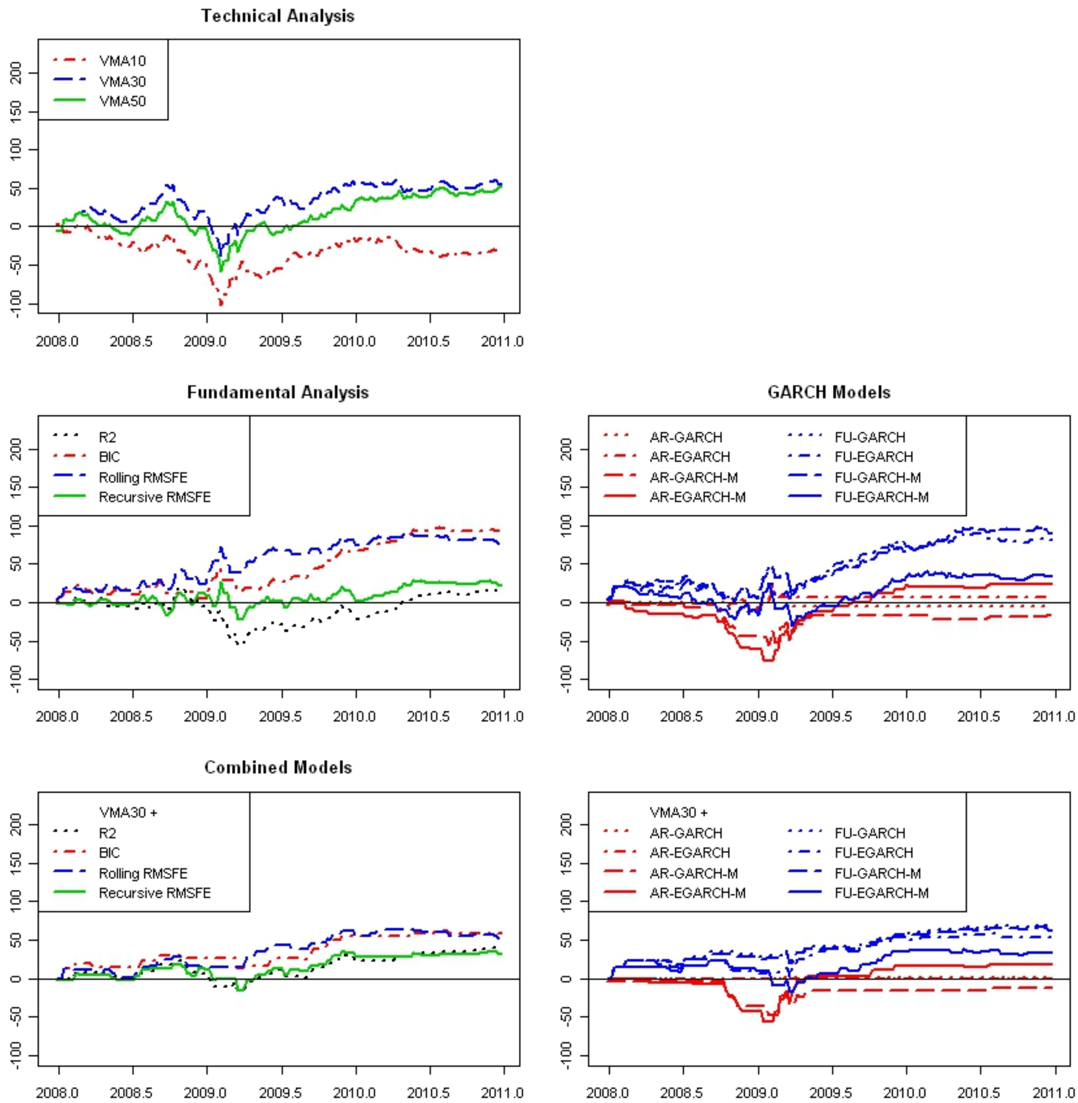
Table 3. Cumulative annual profits with trading signals based on 0.6 % trading filter (2008–2010)

Model		Profits of Positive Return Period	Profits of Negative Return Period	Cumulative Profit / Year
Fundamental Analysis	R2	-5,8 %	10,8 %	4,9 %
	BIC	1,5 %	29,2 %	30,7 %
	Rolling RMSFE	-13,0 %	38,0 %	25,0 %
	Recursive RMSFE	-0,5 %	7,7 %	7,3 %
GARCH Models	AR-GARCH	-13,7 %	12,0 %	-1,6 %
	AR-EGARCH	-9,0 %	11,2 %	2,2 %
	AR-GARCH-M	9,6 %	-15,3 %	-5,7 %
	AR-EGARCH-M	31,9 %	-24,1 %	7,8 %
	FU-GARCH	10,5 %	19,6 %	30,1 %
	FU-EGARCH	13,8 %	13,2 %	26,9 %
	FU-GARCH-M	11,3 %	18,5 %	29,7 %
	FU-EGARCH-M	-16,1 %	27,5 %	11,4 %
Technical Analysis	VMA10	17,5 %	-26,9 %	-9,5 %
	VMA30	22,7 %	-10,6 %	12,2 %
	VMA50	30,8 %	-13,8 %	17,1 %
Combined Models - VMA 30 +	R2	10,0 %	-0,1 %	10,0 %
	BIC	1,8 %	16,7 %	18,5 %
	Rolling RMSFE	3,7 %	11,6 %	15,2 %
	Recursive RMSFE	10,0 %	-2,5 %	7,5 %
	AR-GARCH	0,3 %	0,0 %	0,3 %
	AR-EGARCH	0,2 %	-0,4 %	-0,2 %
	AR-GARCH-M	14,7 %	-18,7 %	-4,0 %
	AR-EGARCH-M	27,7 %	-21,7 %	6,0 %
	FU-GARCH	12,8 %	8,7 %	21,5 %
	FU-EGARCH	15,0 %	2,4 %	17,4 %
	FU-GARCH-M	11,7 %	8,7 %	20,4 %
	FU-EGARCH-M	3,9 %	6,8 %	10,7 %
Number of weeks		86	70	157

Market is informational efficient if profitable trading occurs only locally in time and not with a constant pattern (Timmermann and Granger, 2004). To see how the cumulative profits evolve in our trading simulation, Figure 3 shows the plotted cumulative returns of all trading strategies for the period of 2008–2010. The first impression is an increasing trend in returns at least during 2009, but with varying variance among the strategies. It seems, however, that during 2010 the profits started to even out. Looking at the return accumulation quarterly we find the accumulation rates to lower notably during 2010. Another immediate note is that there are some periods with large profits but also some periods associated with losses with almost all strategies. This is especially the case during the economic turmoil in late 2008 till early 2009 during which time the strategies show a drop in cumulative returns but recovers quickly after that. Table A4 in the Appendix shows the detailed figures for quarterly return accumulation in annual terms. E.g. the BIC-model in the fundamental analysis yields over 30 % cumulative annual profit in total. In the quarterly analyses we find that during the last two quarters there has been almost no profit making at all whereas during the year 2009 the cumulative rates varied between 40–80 % in annual terms. This same trend can be found in most of the models.

The dispersion and variance of the cumulative profits is smallest in the combined models implying that they are the least risky of the models. This is in line with the other results of combined models and their relatively high Sharpe ratios. Based on this observation we conclude that there have been possibilities to trade profitably in the EU ETS market during the study period. Thus, the emerging and young EU ETS market cannot be regarded as an informational efficient market. This finding is based on a relatively short study period. The analysis of informational efficiency would benefit from a longer study period. Thus, the question of the informational efficiency in the EU ETS market remains an interesting question for decades to come.

Figure 3. Cumulative returns of different forecasting models in the EUA trading (January 2008–December 2010).



What drives our results? Figure 4 shows the explanatory variables of the weekly forecasts based on Rolling RMSFE criterion, which proved to be one of the best criteria of the fundamental models. Figure 5 in turn shows the price development of EUA during the study period, which shows one strong decline in price from mid 2008 till the beginning of 2009. We can define periods with three increasing price trends in the EUA price series: the first period is in the very beginning of the period (Q1 2008–Q2 2008), the second period in the first half of 2009 and the last one during the second quarter of 2010. Otherwise the price has been fluctuating rather steadily.

During the price decrease the central economic indicators like FTSE350 and the oil price are included in the variable set. In addition the EUA's own lagged price is strongly present in this downturn period. The second increase that takes place after the long decrease differs from the two other price rises. During the first and last increase demand factors like spread and electricity prices are central variables. In the price increase in early 2009 EUA price lags and volume series dominate the variable set. This might be an indicator of more uncertain traders of the price development after a long downward trend and the general economic sentiment in the economy. During the more stable price periods, like the second half of 2009 and end of 2010, the basic demand variables like electricity prices and fuel prices (gas-coal and oil) are present in the model.

Figure 4. *Explanatory variables and their lags (y-axis) included in Rolling RMSFE models.*

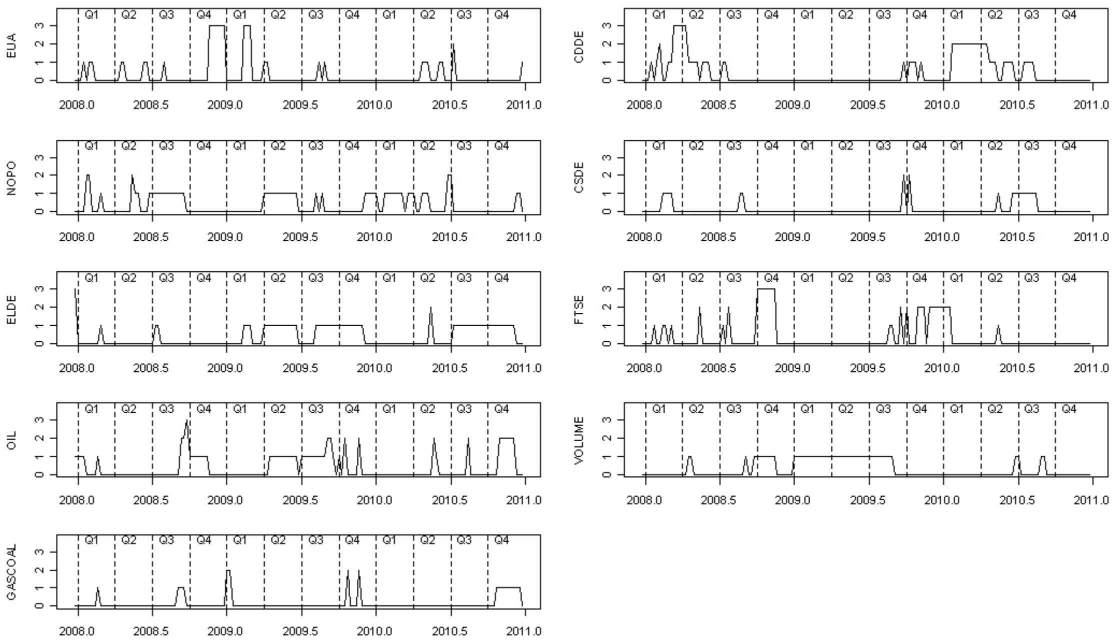
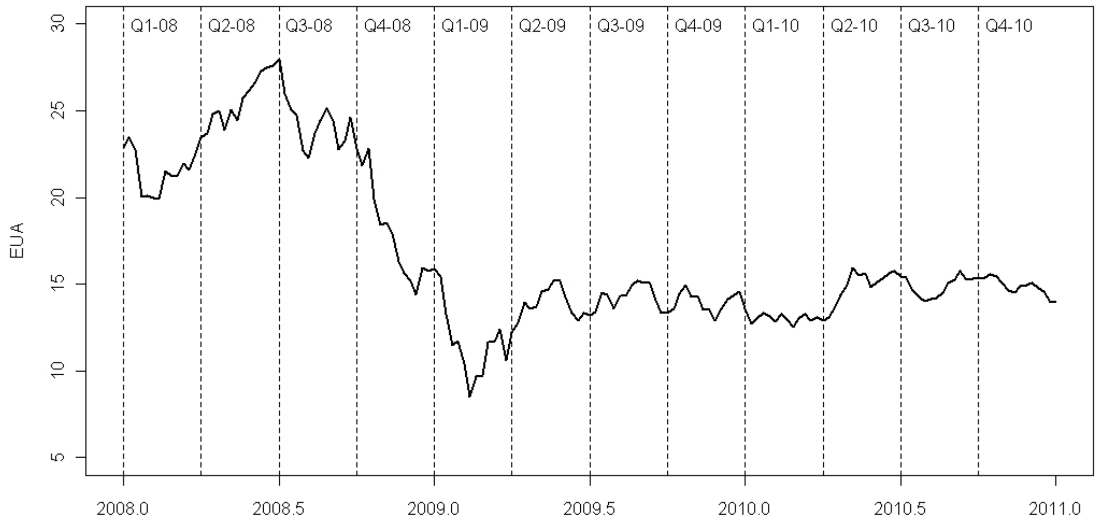


Figure 5. Price of the EUA during the trading period (January 2008–December 2010).



The observation of the rolling RMSFE during 2009, where the non-fundamental variables dominate the model, raises the question of speculative trading and "herding" behaviour in the market. Hinterman (2010) studies the bubbles in the EU ETS market during the first trading period and finds that at least partly the price was driven by this kind of behaviour. In new markets, herding behaviour seems to be stronger due to institutional weaknesses and costly information acquisition, for example. Also in line with our hypothesis, Bikhchandani and Sharma (2000) show with empirical experience that herding seems to be stronger during the bullish market sentiment that is when the price is increasing. A closer investigation of the potential herding behaviour during our study period is, however, beyond the scope of this paper and remains an interesting future research topic.

5. Discussion

Price predictability and profitable trading are a way to study the market informational efficiency (see e.g. Fama, 1991, Timmermann and Granger, 2004). An informational efficient market should not have a predictable price or persistent possibilities of economic profitable trading. For this to happen, the market should have enough actors, high trading volumes and high liquidity. In the EU ETS markets trading volumes and liquidity as well as the number of traders have increased annually during the first trading years. However, the first trading phase included surprises and the price volatility was high due to several reasons. Therefore, the question of informational efficiency in this market is of great interest.

We studied the price predictability and profitable trading by using trading simulation models. With the help of simulations we examined whether traders could have collected profits in the EU ETS markets. We built up different models to reflect the possible trading strategies in the EU ETS market. We run forecasts with time series models based on fundamentals and GARCH terms, technical analysis and combined models of these. We found that there have been some possibilities to trade successfully within the study period. In line with Fang and Xu (2003), we found that technical trading rules were better at identifying the periods of positive returns, whereas the time series models performed better during the periods of price drops.

Based on the results of our simulation model, there are periods when investors could have reaped a profit. The best models yield over 20 % of annual cumulative returns but with relative low Sharpe ratios. This is a clear sign of an emerging market: high profits with relatively high risks. Despite of the profitable trading strategies in terms of cumulative returns, almost all strategies show periods of losses as well. The biggest losses are borne around the global economy turmoil in late 2008 and early 2009.

Contrary to the earlier results of informational efficiency in the EU ETS market by Montagnoli and de Vries (2010) and Miclaus et al. (2008) our results refer to informational inefficient markets. Our analysis applies a different approach with a larger information set compared to these earlier studies. Miclaus et al. (2008) find the market informational efficient during the first period based on event studies. Montagnoli and de Vries (2010) study the weak form of market efficiency and they find the market inefficient during the first period and gaining efficiency in the second period. To assess how robust and important our finding actually is, we have to assess how it relates to an important remark by Timmermann and Granger (2004). They state that the predictability of asset returns, even risk adjusted and covering the transaction costs do not violate the EMH if the predictability exists only locally in time. Once the investors discover a possibility to predict the returns, the possibility disappears rapidly in liquid markets. This argument is reinforced by Malkiel (2003) and Grossmann and Stiglitz (1982), who stress that random profit making is not strong enough evidence to reject the market efficiency hypothesis.

In our analysis, profit making has not been temporary but a rather persistent possibility; the market has not adjusted instantaneously to positive profits. Thus, the reservation of random profits does not apply here. Hence, a provisional conclusion can be made: the EU ETS market has not exhibited informal efficiency during the first and second trading period. While suggesting this conclusion we at the same time admit the obvious limitation of our study. First, our study period is relatively short. As most studies examining informational efficiency include data on several decades, our data set is five years long. Over a longer period of time, profit making may become random as in efficient markets. Secondly, the trading strategies we find to be profitable are chosen based on ex post evaluation. In actual trading, professional traders have to make decisions based on the information they have. In our simulation, we have tried to imitate the model selection of the traders by using some specific rules for model selection. Some of the ex ante trading rules turned out to be profitable but some did not. The problem entails which trading rule to trust. However, the combined trading rules were performing particular well regarding to the riskiness of the trading strategies. If some traders have used similar rules, it is more than probable that they have made actual profits during the first years of the EU ETS.

Our results also reveal interesting research questions for the future. Herding behaviour and market cascades are interesting topics in a novel and politically driven market where new information and learning play a central role. Besides, the EU ETS has participants with various backgrounds and motives, which makes the study of the market efficiency even more interesting. As the market develops and enlarges and becomes more closely linked to other carbon markets, there will be new sources of information and fundamentals affecting the price. This will likely affect the informational efficiency of the market, as well. Thus examining and improving the informational efficiency of the EU ETS market also in the future is important. Only an informational efficient EU ETS market provides means for carrying out a well-functioning economic instrument and hence a cost-efficient climate policy.

References

Alberola E. – Chevallier J. – Cheze B. (2008): Price drivers and structural breaks in European Carbon prices 2005–2007, Energy Policy, 36, 787–797.

Albrecht J. – Verbeke T. – De Clercq M. – (2006): Informational efficiency of the US SO_2 permit market. Environmental Modelling & Software, 21, 1471–1478.

Benz E. – Trück S. (2009): Modelling the Price Dynamics of CO_2 Emission Allowances. Energy Economics, 31, 4–15.

Bikhchandani S. – Sharma S. (2000): Herd Behavior in Financial Markets: A Review. IMF Working Paper No. 00/48.

Bollerslev T. (1986): Generalized autoregressive conditional heteroskedasticity, Journal of Econometrics, 31, 307–327.

Box G. – Jenkins G. (1976): Time series analysis: forecasting and control, rev. ed., Oakland, California: Holden-Day

Chevallier J. (2009): Carbon futures and macroeconomic risk factors: A view from the EU ETS. Energy Economics, 31, 614–625.

Christiansen A C. – Arvanitakis A. – Tangen K. – Hasselknippe H. (2005): Price Determinants in the EU Emissions Trading Scheme. Climate Policy, 5, 15–30.

Conrad C. – Rittler D. – Rotfuss W. (2012): Modeling and explaining the dynamics of European Union Allowance prices at high-frequency. Energy Economics, 34, 316–326.

Creti A. – Jouvet P-A. – Mignon V. (2012): Carbon price drivers: Phase I versus Phase II equilibrium? Energy Economics, 34, 327–334.

Cross F. (1973): The Behavior of Stock Prices on Mondays and Fridays. Financial Analysts Journal, 29, 67–69.

Daskalakis G. – Markellos R. N. (2008): Are the European Carbon Markets Efficient? Review of Futures Markets, 17, 103–128.

Delarue E.D. – D'haeseleer W.D. (2007): Price determination of ETS allowances through the switching level of coal and gas in the power sector. International Journal of Energy Research, 31, 1001–1015.

Dimson E. – Marsh P. – Staunton M. (2002): Triumph of the Optimists: 101 Years of Global Investment Returns. Princeton University Press. Princeton.

Ellerman D. A. – Joskow P. L. (2008): The European Union's Emissions Trading System in perspective. Pew Center on Global Climate Change.

Engle R. (1982): Autoregressive Conditional Heteroscedasticity with Estimates of Variance of United Kingdom Inflation, Econometrica 50, 987–1008.

Engle R. F. – Lilien D. M. – Robins R. P. (1987): Estimating Time-varying Risk Premia in the Term Structure: The ARCH-M Model, Econometrica, 55, 391–408.

Engle R. – Ng V. (1993): Measuring and Testing the Impact of News on Volatility. Journal of Finance, 1993, vol. 48, issue 5, pages 1749–78

Fama E. F. (1965): Random walks in stock prices. Financial Analysts Journal, 21, 55–69.

Fama E. F. (1970): Efficient capital markets: A review of theory and empirical work. Journal of Finance, 25, 383–417.

Fama E. F. (1991): Efficient capital markets: II. The Journal of Finance, 46, 1575–1617

Fang Y. – Xu D. (2003): The predictability of asset returns: an approach combining technical analysis and time series forecasts. International Journal of Forecasting, 19, 369–385.

Fezzi C. – Bunn D.W. (2009): Interaction of European Carbon Trading and Energy Prices, JEM 2(4), 53–69

Gibbons M. – Hess P. (1981): Day of the Week Effects and Asset Returns, Journal of Business, 579–596.

Groenewold N. – Kang K. (1993): The semi-strong efficiency of the Australian Share Market, 69, 405–410.

Gross M. (1988): A semi-strong test of the efficiency of the aluminium and copper markets at the LME. The Journal of Futures Markets, 8, 66–77.

Grossman S. – Stiglitz J. (1982): On the Impossibility of Informationally Efficient Markets. American Economic Review, 70, 393–408.

Hamilton James (1994): Time Series Analysis, Princeton: Princeton Univ. Press,

Hintermann B. (2010): Allowance price drivers in the first phase of the EU ETS. Journal of Environmental Economics and Management, 59, 43–56.

Inoue A. – Kilian L. (2006): On the selection of forecasting models. Journal of Econometrics 130, 273–306

Jaraite J. – Convery F. – Di Maria C. (2010): Assessing the transaction costs of firms in the EU ETS: Lessons from Ireland. Climate Policy, 10, 190–215.

Jensen M. (1978): Some Anomalous Evidence Regarding Market Efficiency. Journal of Financial Economics, 6, 95–101.

Lütkepohl H. (2007): New introduction to Multiple Time Series Analysis. Springer, Berlin.

Malkiel B. (2003): Efficient Market Hypothesis and its critics. Journal of Economic Perspectives, 17, 59–82.

Mansanet-Bataller, A. – Pardo Tornero Á. – Valor E. (2007): CO_2 prices, energy and weather. The Energy Journal, 28, 67–86.

Miclaus P. – Lupu R. – Dumitrescu S. – Bobrica A. (2008): Testing the efficiency of the European Carbon Futures Market using Event-Study Methodology. International Journal of Energy and Management, 2, 121–128.

Milunovich G. – Joyeux R. (2010): Market Efficiency and Price Discovery in the EU Carbon Futures Market. Applied Financial Economics, 20.

Montagnoli A. – de Vries F. P. (2010): Carbon trading thickness and market efficiency, Energy Economics, 32,1331–1336.

Nelson D. (1991): Conditional Heteroskedasticity in Asset Returns: A New Approach. Econometrica, 2, 347–370.

Pagan A. R. – Schwert W. G. (1990): Alternative models for conditional stock volatility. Journal of Econometrics, 45, 267–290.

Paolella MS. – Taschini L. (2008): Econometric Analysis of Emission Trading Allowances. Journal of Banking and Finance, 32.

Pesaran H. – Timmermann A. (1995): Predictability of Stock Returns: Robustness and Economic Significance. The Journal of Finance, 50, 1201–1228.

Pesaran H. – Timmermann A. (2000): A Recursive Modelling approach to predicting UK stock Returns. The Economic Journal , 110, 159–191.

PointCarbon (2010): Providing critical insights into energy and environmental markets. URL: http://www.pointcarbon.com/.

Rickels W. – Duscha V. – Keller A. – Peterson S. (2007): The determinants of allowance prices in the European Emissions Trading Scheme - Can we expect an efficient allowance market 2008? Kiel Working papers, No. 1387.

Roberts H. (1967): Statistical versus clinical prediction of the stock market. Unpublished manuscript. Center for Research in Security prices, University of Chicago.

Sandoff A. – Schaad G. (2009): Does EU ETS lead to emission reductions through trade? The case of the Swedish emissions trading sector participants. Energy Policy, 37, 3967–3977.

State and Trends of Carbon Markets (2010): The Carbon Finance Unit. World Bank. Washington D.C. http://siteresources.worldbank.org/INTCARBONFINANCE/Resources/State_and_Trends_Updated_June_2011.pdf

St. Pierre E.F. (1998): Estimating EGARCH-M Models: Science or Art, The Quarterly Review of Economics and Finance, 38, 167–180.

ThomsonReuters (2010): 3000Xtra Hosted Terminal Access. http://portal.hpd.global.reuters.com.

Timmermann A. – Granger C. (2004): Efficient market hypothesis and forecasting. International Journal of Forecasting, 20, 15–27.

Weigt H. (2009): A Review of Liberalization and Modeling of Electricity Markets. Electricity Markets Working Papers, WP-EM-34. Dresden University of Technology.

Yahoo! Finance (2010): Yahoo! Finance – Business Finance, Stock Market, Quotes, News. http://finance.yahoo.com

Appendix

Table A1a. Descriptive statistics of the log-differenced data

	EUA	NOPO	ELDE	OIL	GASCOAL	CDDE	CSDE	FTSE	VOLUME
Mean	0.00	0.00	0.00	0.00	0.00	-0.07	0.05	0	0
Median	0.00	0.00	0.00	0.00	0.00	-0.05		0	0
Maximum	0.18	0.12	0.15	0.17	0.21	4.13	5.52	0	4
Minimum	-0.21	-0.14	-0.09	-0.15	-0.15	-9.84	-8.40	-0.12	-3.73
Std. Dev.	0.05	0.04	0.03	0.04	0.05	1.36	1.68	0	1
Skewness	-0.39	-0.55	0.27	-0.18	0.58	-1.47	-0.37	-0.60	0.28
Kurtosis	4.79	5.63	7.96	4.55	4.68	14.39	6.23	4.80	10.87
Jarque-Bera	37.41	80.34	245.52	24.93	41.08	1366.63	108.43	46.14	614.34
Probability	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Observations	237	237	237	237	237	237	237	237	237

Table A1b. Cross correlations of the log returns.

	EUA	NOPO	ELDE	OIL	GASCOAL	CDDE	CSDE	FTSE	VOLUME
EUA	1								
NOPO	0.324	1							
ELDE	0.353	0.802	1						
OIL	0.255	0.399	0.345	1					
GASCOAL	0.209	0.121	0.168	0.050	1				
CDDE	0.002	0.104	0.137	-0.137	0.015	1			
CSDE	0.033	-0.079	-0.009	-0.129	-0.094	0.344	1		
FTSE	0.075	0.242	0.141	0.288	-0.041	0.042	0.007	1	
VOLUME	-0.044	-0.055	-0.103	-0.030	0.042	0.038	-0.052	-0.104	1

Table A2a. *Results of the weekly trading simulation with trading signals without a trading filter with pure strategies (1/2008–12/2010)*

	R2	BIC	Rolling R-MSFE	Recursive R-MSFE	AR-GARCH	AR-EGARCH	AR-GARCH-M	AR-EGARCH-M	FU-GARCH	FU-EGARCH	FU-GARCH-M	FU-EGARCH-M
Signals	157	157	157	157	157	157	157	157	157	157	157	157
Buy signals	74	63	60	80	76	53	70	94	81	76	82	57
Sell signals	83	94	97	77	81	104	87	63	76	81	75	100
Winning trades	79	85	86	84	82	73	78	76	90	89	93	79
Profitability index	50,3 %	54,1 %	54,8 %	53,5 %	52,2 %	46,5 %	49,7 %	48,4 %	57,3 %	56,7 %	59,2 %	50,3 %
Profit factor	0,90	1,38	1,52	1,13	1,00	0,79	1,03	1,05	1,32	1,32	1,35	1,07
Average return	-0,21 %	0,60 %	0,77 %	0,23 %	0,00 %	-0,43 %	0,06 %	0,09 %	0,51 %	0,52 %	0,56 %	0,14 %
Cu-Mulative profit / year	-10,8 %	31,2 %	40,2 %	12,2 %	0,0 %	-22,5 %	3,2 %	4,6 %	26,6 %	26,8 %	28,9 %	7,1 %
Sharpe ratio	-0,04	0,11	0,15	0,04	0,00	-0,08	0,01	0,02	0,10	0,10	0,11	0,03

	V-MA10	V-MA30	V-MA50
Signals	157	157	157
Buy signals	86	75	79
Sell signals	71	82	78
Winning trades	71	78	80
Profitability index	45,2 %	49,7 %	51,0 %
Profit factor	0,91	1,20	1,17
Average return	-0,18 %	0,34 %	0,29 %
Cumulative profit / year	-9,4 %	17,5 %	15,3 %
Sharpe ratio	-0,03	0,06	0,06

Table A2b. *Results of the weekly trading simulation with trading signals without a trading filter with combined strategies (1/2008–12/2010)*

V-MA30 +	R2	BIC	Rolling R-MSFE	Recursive R-MSFE	AR-GARCH	AR-EGARCH	AR-GARCH-M	AR-EGARCH-M	FU-GARCH	FU-EGARCH	FU-GARCH-M	FU-EGARCH-M
Signals	70	65	68	70	46	61	90	78	67	74	66	77
Buy signals	31	23	23	34	20	16	39	45	33	34	33	26
Sell signals	39	42	45	36	26	45	51	33	34	40	33	51
Winning trades	35	36	38	38	25	28	45	38	39	42	40	39
Profitability index	50,0 %	55,4 %	55,9 %	54,3 %	54,3 %	45,9 %	50,0 %	48,7 %	58,2 %	56,8 %	60,6 %	50,6 %
Profit factor	1,08	1,89	2,09	1,38	1,39	0,93	1,19	1,22	1,74	1,58	1,80	1,30
Average return	0,14 %	1,13 %	1,28 %	0,64 %	0,57 %	-0,12 %	0,35 %	0,43 %	0,99 %	0,90 %	1,06 %	0,48 %
Cumulative profit / year	3,4 %	24,3 %	28,9 %	14,8 %	8,8 %	-2,5 %	10,4 %	11,0 %	22,1 %	22,2 %	23,2 %	12,3 %
Sharpe ratio	0,02	0,14	0,19	0,08	0,07	-0,02	0,05	0,05	0,12	0,11	0,13	0,06

Table A3. *Results of the weekly trading simulation with trading signals based on 0.6 % trading filter – additional combined models (January 2008–December 2010)*

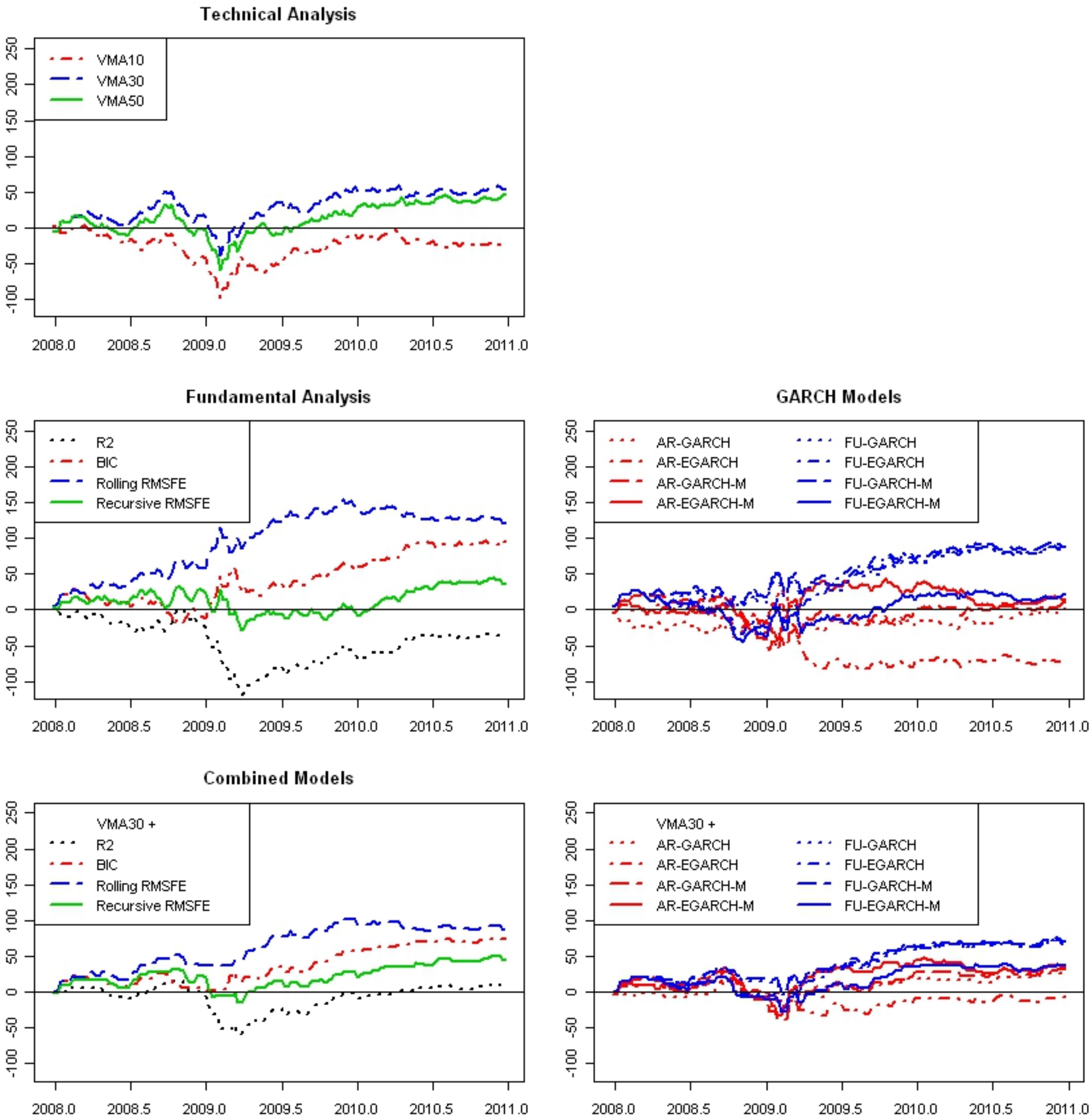
VMA10 +	R2	BIC	Rolling RMSFE	Recursive RMSFE	AR-GARCH	AR-EGARCH	AR-GARCH-M	AR-EGARCH-M	FU-GARCH	FU-EGARCH	FU-GARCH-M	FU-EGARCH-M
Signals	41	25	35	44	2	2	13	26	41	46	41	45
Buy signals	20	9	18	23	2	2	13	23	23	25	23	15
Sell signals	21	16	17	21	0	0	0	3	18	21	18	30
Winning trades	20	16	18	21	2	1	6	13	22	24	23	23
Profitability index	48.8 %	64.0 %	51.4 %	47.7 %	100.0 %	50.0 %	46.2 %	50.0 %	53.7 %	52.2 %	56.1 %	51.1 %
Profit factor	1.15	3.94	1.39	1.13	inf	0.49	0.51	1.21	1.84	1.41	1.82	1.07
Average return	0.22 %	**1.81 %**	0.51 %	0.23 %	0.52 %	-0.32 %	-1.80 %	0.55 %	**0.91 %**	**0.64 %**	**0.93 %**	0.12 %
Cumulative profit / year	3.1 %	14.9 %	5.9 %	3.4 %	0.3 %	-0.2 %	-7.7 %	4.7 %	12.4 %	9.8 %	12.6 %	1.7 %
Sharpe ratio	0.03	0.19	0.06	0.03	0.09	-0.05	-0.06	0.03	0.12	0.07	0.12	0.01

VMA50 +	R2	BIC	Rolling RMSFE	Recursive RMSFE	AR-GARCH	AR-EGARCH	AR-GARCH-M	AR-EGARCH-M	FU-GARCH	FU-EGARCH	FU-EGARCH	FU-GARCH-M
Signals	42	29	37	41	2	2	29	42	42	43	42	52
Buy signals	22	9	14	22	2	2	22	34	21	22	21	19
Sell signals	20	20	23	19	0	0	7	8	21	21	21	33
Winning trades	24	19	21	21	2	1	18	25	28	27	28	29
Profitability index	57.1 %	65.5 %	56.8 %	51.2 %	100.0 %	50.0 %	62.1 %	59.5 %	66.7 %	62.8 %	66.7 %	55.8 %
Profit factor	1.51	2.42	2.10	1.27	inf	0.49	0.90	1.38	2.93	2.18	2.72	1.41
Average return	**0.88 %**	**1.83 %**	**1.38 %**	0.55 %	0.52 %	-0.32 %	-0.23 %	**0.79 %**	**1.98 %**	**1.71 %**	**1.90 %**	**0.66 %**
Cumulative profit / year	12.2 %	17.5 %	16.9 %	7.4 %	0.3 %	-0.2 %	-2.2 %	11.0 %	27.6 %	24.3 %	26.5 %	11.3 %
Sharpe ratio	0.08	0.14	0.14	0.05	0.09	-0.05	-0.02	0.06	0.20	0.15	0.19	0.07

Table A4. Quarterly cumulative profits in annual terms

	Q1-08	Q2-08	Q3-08	Q4-08	Q1-09	Q2-09	Q3-09	Q4-09	Q1-10	Q2-10	Q3-10	Q4-10	All
R2	-17 %	-5 %	8 %	-5 %	-203 %	106 %	35 %	21 %	13 %	82 %	5 %	18 %	4,9 %
BIC	64 %	6 %	8 %	-61 %	41 %	50 %	70 %	84 %	49 %	52 %	1 %	0 %	30,7 %
Rolling RMSFE	53 %	9 %	27 %	10 %	55 %	119 %	4 %	45 %	16 %	3 %	-17 %	-24 %	25,0 %
Recursive RMSFE	-23 %	13 %	-28 %	87 %	-137 %	92 %	13 %	15 %	18 %	48 %	-8 %	-4 %	7,3 %
AR-GARCH	-1 %	0 %	0 %	-27 %	68 %	-60 %	0 %	0 %	0 %	0 %	0 %	0 %	-1,6 %
AR-GARCH-M	-14 %	0 %	-3 %	-157 %	15 %	91 %	-3 %	0 %	-15 %	-5 %	14 %	9 %	-5,7 %
AR-EGARCH	-5 %	0 %	0 %	-34 %	66 %	0 %	0 %	0 %	0 %	0 %	0 %	0 %	2,2 %
AR-EGARCH-M	-44 %	-16 %	-10 %	-173 %	44 %	151 %	51 %	60 %	17 %	-7 %	18 %	0 %	7,8 %
FU-GARCH	71 %	25 %	-21 %	-38 %	64 %	36 %	80 %	44 %	66 %	48 %	1 %	-16 %	30,1 %
FU-GARCH-M	62 %	13 %	-5 %	-38 %	64 %	36 %	80 %	44 %	66 %	48 %	1 %	-16 %	29,7 %
FU-EGARCH	89 %	21 %	-32 %	-136 %	62 %	155 %	89 %	63 %	2 %	39 %	-41 %	10 %	26,9 %
FU-EGARCH-M	39 %	-14 %	-39 %	-26 %	-22 %	42 %	66 %	62 %	43 %	-17 %	-19 %	18 %	11,4 %
VMA10	-18 %	-84 %	28 %	-108 %	-57 %	21 %	67 %	93 %	0 %	-74 %	-11 %	-6 %	-11,7 %
VMA30	106 %	-84 %	139 %	-108 %	-122 %	192 %	-5 %	87 %	-18 %	-26 %	2 %	18 %	18,2 %
VMA50	44 %	-84 %	139 %	-108 %	-122 %	99 %	65 %	72 %	32 %	16 %	12 %	35 %	17,1 %
VMA30-BIC	79 %	-21 %	60 %	-13 %	-58 %	54 %	48 %	64 %	0 %	13 %	-2 %	0 %	19,2 %
VMA30-R2	29 %	-26 %	58 %	-50 %	-98 %	112 %	13 %	63 %	-25 %	39 %	7 %	12 %	12,6 %
VMA30-Rolling RMSFE	45 %	-39 %	76 %	-35 %	0 %	112 %	7 %	64 %	3 %	-11 %	-19 %	-16 %	16,9 %
VMA30-Recursive RMSFE	20 %	-27 %	48 %	-2 %	-114 %	112 %	16 %	63 %	-25 %	10 %	4 %	0 %	10,1 %
VMA30-AR-GARCH	0 %	0 %	0 %	0 %	4 %	0 %	0 %	0 %	0 %	0 %	0 %	0 %	0,3 %
VMA30-AR-GARCH-M	-18 %	0 %	0 %	-127 %	5 %	74 %	0 %	0 %	0 %	0 %	18 %	0 %	-4,0 %
VMA30-AR-EGARCH	0 %	0 %	0 %	-5 %	2 %	0 %	0 %	0 %	0 %	0 %	0 %	0 %	-0,2 %
VMA30-AR-EGARCH-M	-4 %	-19 %	-8 %	-143 %	52 %	134 %	0 %	46 %	0 %	-7 %	18 %	0 %	6,0 %
VMA30-FU-GARCH	88 %	-17 %	65 %	-13 %	-34 %	76 %	15 %	45 %	23 %	10 %	8 %	-11 %	21,5 %
VMA30-FU-GARCH-M	88 %	-30 %	65 %	-13 %	-34 %	76 %	15 %	45 %	23 %	10 %	8 %	-11 %	20,4 %
VMA30-FU-EGARCH	88 %	-11 %	50 %	-93 %	-34 %	154 %	27 %	42 %	-12 %	10 %	-8 %	-5 %	17,4 %
VMA30-FU-EGARCH-M	57 %	-17 %	50 %	-42 %	-117 %	93 %	44 %	64 %	8 %	-11 %	-8 %	3 %	10,7 %

Figure A1. *Cumulative returns without a trading filter for 2008–2010*



IN VATT WORKING PAPERS SERIES PUBLISHED PUBLICATIONS

8. Katariina Nilsson Hakkala – Fredrik Heyman – Fredrik Sjöholm: Multinational firms and job tasks. Helsinki 2009.
9. Seppo Kari – Hanna Karikallio – Jukka Pirttilä: The impact of dividend taxation on dividends and investment: New evidence based on a natural experiment. Helsinki 2009.
10. Sara Ayllón: Modelling state dependence and feedback effects between poverty, employment and parental home emancipation among European youth. Helsinki 2009.
11. Juha Honkatukia – Jouko Kinnunen – Kimmo Marttila: Distributional effects of Finland's climate policy package – Calculations with the new income distribution module of the VATTAGE model. Helsinki 2009.
12. Juha Tuomala: The threat effect of mandatory programme participation in Finland – A study of activation reform of the labour market support system. Helsinki 2010.
13. Ilja Kristian Kavonius: Fiscal policies in Europe and the United States during the Great Depression. Helsinki 2010.
14. Miikka Rokkanen – Roope Uusitalo: Changes in job stability – evidence from lifetime job histories. Helsinki 2010.
15. Heléne Lundqvist: Granting public or private consumption? Effects of grants on local public spending and income taxes. Helsinki 2010.
16. Ossi Korkeamäki – Tomi Kyyrä: Institutional rules, labour demand and retirement through disability programme participation. Helsinki 2010.
17. Tomi Kyyrä: Early retirement policy in the presence of competing exit pathways: Evidence from policy reforms in Finland. Helsinki 2010.
18. Tuomas Kosonen: What was actually cut in the barbers' VAT cut? Helsinki 2010.
19. Tuukka Saarimaa – Janne Tukiainen: Coalition formation and political decision making: Evidence from Finnish municipal mergers. Helsinki 2010.
20. Teemu Lyytikäinen – Torsten Santavirta: The effect of church tax on church membership. Helsinki 2010.
21. Tomi Kyyrä – Ralf A. Wilke: On the reliability of retrospective unemployment information in European household panel data. Helsinki 2011.
22. Ossi Korkeamäki: The Finnish payroll tax cut experiment revisited. Helsinki 2011.
23. Tuomas Kosonen: To work or not to work? The effect of child-care subsidies on the labour supply of parents. Helsinki 2011.
24. Olli Ropponen: Reconciling the evidence of Card and Krueger (1994) and Neumark and Wascher (2000). Helsinki 2011.
25. Olli Ropponen: A Note on the Robustness of Card and Krueger (1994) and Neumark and Wascher (2000). Helsinki 2011.
26. Teemu Lyytikäinen: Tax competition among local governments: evidence from a property tax reform in Finland. Helsinki 2011.
27. Jarkko Harju – Seppo Kari: Dividend taxes and decision of MNEs: Evidence from a Finnish tax reform. Helsinki 2011.

VALTION TALOUDELLINEN TUTKIMUSKESKUS
STATENS EKONOMISKA FORSKNINGSCENTRAL
GOVERNMENT INSTITUTE FOR ECONOMIC RESEARCH

Valtion taloudellinen tutkimuskeskus
Government Institute for Economic Research
P.O.Box 1279
FI-00101 Helsinki
Finland

ISBN 978-952-274-016-8
ISSN 1798-0291

9 789522 740151